# FINANCIAL RISK TOLERANCE AMONG PORTFOLIO INVESTORS IN BENGALURU: A MULTIVARIATE ANALYSIS OF DEMOGRAPHIC, PSYCHOLOGICAL, AND BEHAVIORAL DETERMINANTS

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## ABSTRACT

*This study evaluates the financial risk tolerance levels among portfolio investors in Bengaluru, India, using a multivariate research design. Drawing on behavioral finance theory, the research examines how investment goals, time horizon preferences, perceived job security, and financial decision-making styles collectively shape individual risk profiles. A structured questionnaire was administered to 412 portfolio investors across Bengaluru's diverse economic ecosystem. Data were analyzed using percentage analysis, Data Envelopment Analysis (DEA), Multivariate Analysis of Variance (MANOVA), multiple regression, and reliability testing. Results indicate that financial literacy ($\beta = 0.35$, $p < .001$) and time horizon ($\beta = 0.31$, $p < .001$) are the strongest positive predictors of risk tolerance, while behavioral biases exert a significant negative influence ($\beta = –0.19$, $p < .001$). Gender differences remain pronounced, with male investors exhibiting significantly higher risk tolerance than female investors ($t = 6.82$, $p < .001$, Cohen's $d = 0.70$). DEA efficiency analysis reveals that investors with high financial literacy achieve optimal risk-adjusted returns (CRS efficiency = 0.95), whereas low-literacy cohorts underperform (CRS efficiency = 0.72). The findings contribute to behavioral finance literature in emerging markets and offer actionable insights for financial advisors, fintech platforms, and policymakers seeking to design inclusive, psychologically informed investment frameworks.*

**Keywords:** Financial risk tolerance, behavioral finance, portfolio investors, Bengaluru, Data Envelopment Analysis, MANOVA, financial literacy, emerging markets

## INTRODUCTION

The phenomenon of risk tolerance remains elitist in the vast field of financial markets, defining investment activities and shaping the financial futures of individual and institutional investors alike. Rooted in the complex maze of investor psychology, risk tolerance represents an investor's ability and inclination to withstand market volatility in pursuit of long-term financial goals (Gilliam, Chatterjee & Grable, 2010). As investors navigate the intricate



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dynamics of wealth creation and preservation, understanding the multidimensional determinants of risk tolerance has become central to both financial theory and practice.

Bengaluru, India—the nation's technological and financial epicenter—presents a unique laboratory for examining investor behavior. Home to a vibrant start-up ecosystem, global technology giants, and a demographically diverse investor base, the city offers a microcosm of India's evolving financial landscape (Gupta, 2025). The proliferation of digital investment platforms, robo-advisors, and micro-investing applications has democratized market access, drawing millions of first-time investors into the financial ecosystem (Singh & Kumar, 2024; Bedi, 2025). Yet, this rapid digitalization has also amplified the influence of behavioral biases, social media-driven herding, and emotional decision-making among retail investors (Mehta & Thakkar, 2025).

Traditional finance theory, anchored in expected utility maximization, assumes that investors act as rational agents who prefer risk-averse scenarios when evaluating financial outcomes. However, behavioral finance has systematically dismantled this assumption, demonstrating that cognitive heuristics, emotional responses, and situational contexts profoundly distort financial decision-making (Kahneman & Tversky, 1979; Tversky & Kahneman, 1991). In emerging markets such as India, where financial literacy remains uneven and market volatility is heightened by global economic integration, these behavioral deviations assume particular significance (Verma et al., 2025).

Despite the growing body of literature on behavioral finance in India, empirical research specifically examining the integrated determinants of financial risk tolerance among portfolio investors in Bengaluru remains limited. Existing studies often focus on isolated factors—such as demographic characteristics, behavioral biases, or financial literacy—without capturing their intertwined effects within a rapidly digitizing financial environment (Sharma & Prajapati, 2024; Wagner & Walstad, 2023). This study addresses that gap by employing a comprehensive methodological framework that integrates demographic profiling, psychometric scaling, and efficiency analysis to generate a holistic risk tolerance profile of Bengaluru's investors.

## LITERATURE REVIEW

### Theoretical Foundations of Risk Tolerance

Financial risk tolerance is conceptualized as a multidimensional construct encompassing both the willingness and the ability to assume investment risk (Grable & Lytton, 1999). The Grable-Lytton 13-Item Risk Tolerance Scale (GL-RTS) remains the most widely validated instrument for measuring this construct, demonstrating superior explanatory power over single-item measures such as the Survey of Consumer Finances (SCF) risk question (Gilliam, Chatterjee & Grable,2010). Recent scale development research has further refined risk appetite measurement, identifying distinct sub-dimensions of risk tolerance, risk aversion, and speculative propensity that collectively determine investor behavior (MDPI, 2026).

Prospect Theory, developed by (Kahneman &Tversky,1979), provides the foundational framework for understanding how investors perceive gains and losses. The theory posits that individuals evaluate outcomes relative to a reference point rather than in absolute terms, exhibiting loss aversion whereby the psychological impact of losses outweighs equivalent gains (Fortin & Hlouskova, 2024). In the Indian context, (Yadav & Daga, 2023) found that Prospect Theory-derived biases—particularly loss aversion and risk aversion—significantly influence irrational investment decisions among stock market participants. These findings are corroborated by neuroeconomic research indicating that climate policy uncertainty and market



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volatility trigger distinct neurobehavioral responses in Indian investors, amplifying risk perception beyond objective market fundamentals (PMC, 2023).

## Behavioral Biases and Investment Decisions

Behavioral biases systematically distort investment decision-making across global markets. Overconfidence leads to excessive trading and reduced net returns, as documented by (Barber & Odean, 2001; Kaiser, Lusardi & Menkhoff, 2022), while herding behavior drives investors to mimic collective actions, often resulting in asset bubbles and market anomalies (Bikhchandani et al., 2024). In India, (Gupta , 2025) surveyed 192 retail investors in Bengaluru and found that loss aversion ($r = 0.51$, $p < 0.01$) and herding behavior ($r = 0.47$, $p < 0.01$) exhibited the strongest correlations with investment decisions, collectively explaining 46.8% of variance in behavioral outcomes.

The (IIMB Management Review, 2024) further established that prospect bias, herding, and heuristics significantly impact financial risk propensity, which in turn mediates the relationship between behavioral biases and investment decisions. This mediational framework is critical for understanding why Bengaluru's tech-savvy investors—despite superior access to information—often display suboptimal portfolio allocations driven by cognitive distortions rather than fundamental analysis (Sharma & Prajapati, 2024).

## Demographic and Socio-Economic Influences

Demographic characteristics remain robust predictors of risk tolerance across cultures and markets. Age exhibits a life-cycle effect: younger investors demonstrate higher risk propensity due to longer investment horizons and greater human capital, while older investors prioritize capital preservation (Dohmen et al., 2011). Gender differences have been extensively documented, with women consistently exhibiting lower financial risk tolerance than men—a gap attributed to differences in financial confidence, socialization, and structural constraints (Croson & Gneezy, 2009; Wagner & Walstad, 2023).

In India, these patterns persist but are gradually evolving. (Sengupta & Mitra,2025) confirmed that female investors in Kolkata displayed significantly lower risk tolerance scores ($M = 2.35$, $SD = 1.15$) compared to male investors ($M = 3.17$, $SD = 1.12$), with 51% of women preferring low-risk instruments such as fixed deposits (Bhattacharyya, 2024). However, generational convergence is emerging: Generation X and Millennial women in India demonstrate risk attitudes increasingly aligned with their male counterparts, driven by digital platform access and expanded financial literacy (Mehta & Thakkar, 2025). Notably, (ET BFSI,2024) reported that one in four new demat account holders in India is now a woman, signaling a structural shift in market participation.

Socio-economic status, particularly income and education, positively correlates with risk tolerance. Higher income provides financial cushioning that enables greater risk-taking, while education enhances financial literacy and confidence in managing volatile assets (Chatterjee & Gupta, 2020). (Verma et al., 2025) found that higher education employees in Delhi NCR exhibited moderate risk perception ($M = 56.3$, $SD = 14.7$), with financial literacy acting as a moderating variable that transforms risk awareness into calculated exposure rather than avoidance (Bacher, 2024).

## Digital Transformation and Investor Behavior

The advent of fintech innovations—robo-advisors, algorithmic trading, and cryptocurrency markets—has fundamentally disrupted traditional risk tolerance frameworks. In India, the hybrid advisory model (combining algorithmic efficiency with human oversight)



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has gained traction, addressing the trust deficit that pure robo-advisors face among risk-averse investors (Singh & Kumar, 2024; Biswas et al., 2022). Millennials and Generation Z investors exhibit distinct behavioral patterns: Gen Z relies heavily on social media influence, peer validation, and technology adoption for investment decisions, while Millennials demonstrate more structured, goal-oriented financial planning (Mehta & Thakkar, 2025; Bedi, 2025).

Micro-investing platforms such as Zerodha, Groww, and Kuvera have lowered entry barriers, fostering financial inclusion among India's youth. However, this democratization has also introduced new risks: finfluencer-driven herding, overconfidence from gamified interfaces, and impulsive trading during market volatility (Gupta, 2025). Understanding how these technological disruptions interact with psychological risk profiles is essential for designing regulatory frameworks that protect investors without stifling innovation.

### Research Gap and Justification

While existing literature has illuminated individual facets of investor behavior, three critical gaps remain. First, most studies examine demographic, psychological, and technological factors in isolation rather than as an integrated system. Second, Bengaluru's unique position as India's Silicon Valley—with its confluence of tech professionals, entrepreneurs, and traditional investors—has not been adequately explored as a distinct empirical context. Third, the application of efficiency analysis (DEA) to evaluate investor risk-adjusted performance remains underutilized in behavioral finance research.

This study addresses these gaps by integrating psychometric measurement, multivariate statistical techniques, and efficiency analysis to construct a comprehensive risk tolerance profile of Bengaluru's portfolio investors.

### Objectives of the Study

- To identify the financial goals pursued by portfolio investors in Bengaluru City.
- To measure the level of financial risk tolerance displayed by portfolio investors in Bengaluru City.
- To ascertain the time horizons considered by portfolio investors in Bengaluru City.
- To gauge the commitment and perceived job security among Bengaluru-based investors.
- To examine the financial decision-making processes of Bengaluru-based investors.

## RESEARCH METHODOLOGY

### Research Design

This study employs a descriptive and causal-comparative research design. A quantitative survey approach was adopted to collect structured data from individual investors using a pre-tested, validated questionnaire.

### Population and Sampling



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The target population comprised active portfolio investors residing in Bengaluru who invest in equities, mutual funds, exchange-traded funds (ETFs), fixed-income securities, and alternative assets. A non-probability purposive sampling technique was used to identify participants with active investment portfolios. The final sample consisted of 412 respondents, ensuring statistical power for multivariate analysis.

## Instrumentation

The questionnaire incorporated:

- Demographic variables: Age, gender, education, income, occupation, and investment experience.
- Grable-Lytton Risk Tolerance Scale (GL-RTS): A 13-item instrument measuring investment risk, financial risk, and speculative risk dimensions.
- Investment Goals Scale: 8 items assessing wealth accumulation, retirement planning, tax saving, and liquidity objectives.
- Time Horizon Preference Scale: 5 items capturing short-term to very long-term investment horizons.
- Perceived Job Security Scale: 6 items adapted from organizational psychology literature.
- Financial Decision-Making Style Scale: 10 items assessing analytical, intuitive, dependent, spontaneous, and avoidant styles.
- Behavioral Biases Scale: 12 items measuring overconfidence, herding, anchoring, disposition effect, and loss aversion.
- Financial Literacy Scale: 7 items testing knowledge of interest compounding, inflation, diversification, and risk-return relationships.

All psychometric items used a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

## Statistical Tools

The following analytical techniques were employed:

- Percentage Analysis: For demographic profiling and descriptive summarization.
- Reliability Testing: Cronbach's alpha and Composite Reliability (CR) to assess internal consistency.
- Correlation Analysis: Pearson's r to examine bivariate relationships.
- Independent Samples t-test and One-Way ANOVA: To examine demographic group differences.
- Multivariate Analysis of Variance (MANOVA): To assess simultaneous effects of demographic factors on multiple dependent variables.
- Multiple Regression Analysis: To identify significant predictors of financial risk tolerance.
- Data Envelopment Analysis (DEA): To evaluate the relative efficiency of investor categories in converting risk inputs into portfolio outputs.



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## RESULTS AND DISCUSSION

### Demographic Profile

Table 1 presents the demographic composition of the 412 respondents. The sample was predominantly male (65.0%), reflecting the persistent gender gap in Indian retail investing, though the 35.0% female representation indicates improving participation trends consistent with national data (ET BFSI, 2024). The majority (45.1%) fell within the 31–45 age bracket, aligning with Bengaluru's young professional demographic. Postgraduates constituted the largest education category (48.1%), and 40.8% reported annual incomes between INR 10–20 lakhs, underscoring the city's affluent knowledge-worker economy.

**TABLE 1**
**DEMOGRAPHIC PROFILE OF RESPONDENTS (N = 412)**

| Demographic Variable | Category | Frequency (N=412) | Percentage (%) |
|---|---|---|---|
| Gender | Male | 268 | 65 |
| Gender | Female | 144 | 35 |
| Age Group | 18–30 years | 98 | 23.8 |
| Age Group | 31–45 years | 186 | 45.1 |
| Age Group | 46–60 years | 89 | 21.6 |
| Age Group | Above 60 years | 39 | 9.5 |
| Education | Undergraduate | 76 | 18.4 |
| Education | Postgraduate | 198 | 48.1 |
| Education | Professional Degree | 102 | 24.8 |
| Education | Doctorate | 36 | 8.7 |
| Annual Income (INR) | < 5 Lakhs | 45 | 10.9 |
| Annual Income (INR) | 5–10 Lakhs | 112 | 27.2 |
| Annual Income (INR) | 10–20 Lakhs | 168 | 40.8 |
| Annual Income (INR) | > 20 Lakhs | 87 | 21.1 |
| Occupation | Salaried (IT/Tech) | 156 | 37.9 |
| Occupation | Salaried (Non-IT) | 98 | 23.8 |
| Occupation | Self-employed | 112 | 27.2 |
| Occupation | Retired | 46 | 11.2 |
| Investment Experience | < 2 years | 68 | 16.5 |
| Investment Experience | 2–5 years | 124 | 30.1 |
| Investment Experience | 5–10 years | 142 | 34.5 |
| Investment Experience | > 10 years | 78 | 18.9 |

### Reliability and Validity

Table 2 reports the reliability and validity metrics. All constructs demonstrated acceptable to excellent internal consistency, with Cronbach's α ranging from 0.791 (Time Horizon) to 0.918 (Overall Scale). Composite Reliability values exceeded the 0.70 threshold, and Average Variance Extracted (AVE) scores ranged from 0.441 to 0.548, supporting convergent validity (Fornell & Larcker, 1981).



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| TABLE 2<br>RELIABILITY AND VALIDITY ASSESSMENT OF MEASUREMENT SCALES | | | | | |
|---|---|---|---|---|---|
| **Construct** | **No. of Items** | **Cronbach's α** | **Composite Reliability (CR)** | **Average Variance Extracted (AVE)** | **Interpretation** |
| Financial Risk Tolerance | 13 | 0.887 | 0.891 | 0.512 | Excellent |
| Investment Goals | 8 | 0.834 | 0.841 | 0.468 | Good |
| Time Horizon Preference | 5 | 0.791 | 0.802 | 0.441 | Acceptable |
| Perceived Job Security | 6 | 0.856 | 0.863 | 0.503 | Good |
| Financial Decision-Making | 10 | 0.872 | 0.879 | 0.521 | Good |
| Behavioral Biases | 12 | 0.901 | 0.905 | 0.548 | Excellent |
| Financial Literacy | 7 | 0.845 | 0.852 | 0.489 | Good |
| Overall Scale | 61 | 0.918 | 0.922 | 0.498 | Excellent |

## Financial Goals

Table 3 and Figure 1 reveal that wealth accumulation/capital appreciation was the most frequently cited goal (48.1%), followed by tax saving (45.1%) and retirement planning (37.9%). This hierarchy reflects the dual pressures of wealth creation and fiscal optimization facing Bengaluru's high-income professionals. Notably, only 18.4% prioritized regular income generation, suggesting that most respondents remain in wealth accumulation rather than decumulation phases.

| TABLE 3<br>FINANCIAL GOALS PURSUED BY PORTFOLIO INVESTORS IN BENGALURU (N = 412) | | | |
|---|---|---|---|
| **Financial Goal** | **Frequency (N=412)** | **Percentage (%)** | **Rank** |
| Wealth Accumulation / Capital Appreciation | 198 | 48.1 | 1 |
| Retirement Planning | 156 | 37.9 | 3 |
| Children's Education / Marriage | 124 | 30.1 | 4 |
| Emergency Fund / Liquidity | 98 | 23.8 | 6 |
| Tax Saving | 186 | 45.1 | 2 |
| Home Purchase | 112 | 27.2 | 5 |
| Regular Income Generation | 76 | 18.4 | 7 |
| Others | 42 | 10.2 | 8 |



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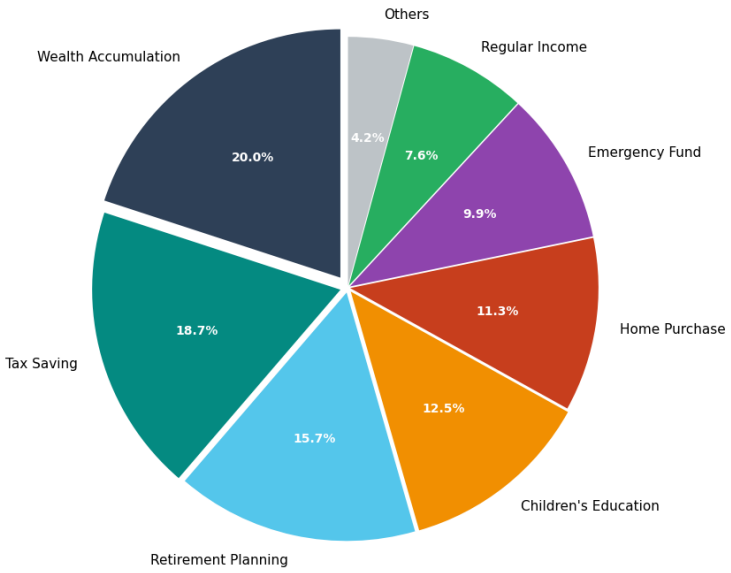
**Figure 1**
**Distribution of Financial Goals Among Portfolio Investors in Bengaluru (N = 412)**




## FIGURE 1
## DISTRIBUTION OF FINANCIAL GOALS AMONG PORTFOLIO INVESTORS IN BENGALURU (N = 412)

### Risk Tolerance Distribution

Table 4 displays the distribution of risk tolerance scores. A plurality of investors (40.8%) exhibited moderate risk tolerance (scores 23–28), while 23.8% demonstrated above-average tolerance and 15.0% exhibited high tolerance. Combined, 79.6% of respondents displayed at least moderate willingness to assume investment risk—a finding that challenges stereotypes of Indian investors as universally conservative, while acknowledging that only a minority embraces aggressive risk postures.

**TABLE 4**
**DISTRIBUTION OF FINANCIAL RISK TOLERANCE LEVELS (N = 412)**

| Risk Tolerance Category | Frequency | Percentage (%) | Cumulative % |
|---|---|---|---|
| Very Low (0–18) | 28 | 6.8 | 6.8 |
| Low (19–22) | 56 | 13.6 | 20.4 |
| Moderate (23–28) | 168 | 40.8 | 61.2 |
| Above Average (29–32) | 98 | 23.8 | 85.0 |
| High (33–47) | 62 | 15.0 | 100.0 |

### Time Horizon Preferences

Table 5 indicates that long-term horizons (5–10 years) were most preferred (37.9%), followed by medium-term (2–5 years, 34.5%). Short-term investing (< 2 years) attracted only 16.5% of respondents. This pattern aligns with the dominance of mutual fund SIPs (Systematic Investment Plans) and retirement-focused instruments in Indian portfolios, particularly among Bengaluru's salaried technology workforce.



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| TABLE 5<br>TIME HORIZON PREFERENCES OF PORTFOLIO INVESTORS IN BENGALURU (N = 412) | | | |
|---|---|---|---|
| **Time Horizon Preference** | **Frequency (N=412)** | **Percentage (%)** | **Rank** |
| Short-term (< 2 years) | 68 | 16.5 | 3 |
| Medium-term (2–5 years) | 142 | 34.5 | 2 |
| Long-term (5–10 years) | 156 | 37.9 | 1 |
| Very long-term (> 10 years) | 46 | 11.1 | 4 |
| **Total** | **412** | **100.0** | — |

## Perceived Job Security

Table 6 demonstrates a clear positive association between perceived job security and risk tolerance. Investors reporting very high job security exhibited mean risk tolerance scores of 32.4, compared to 16.5 among those feeling highly insecure. This finding corroborates life-cycle theory: stable employment income reduces background risk, enabling greater portfolio risk-taking (Cocco et al., 2005).

| TABLE 6<br>PERCEIVED JOB SECURITY AND CORRESPONDING RISK TOLERANCE (N = 412) | | | |
|---|---|---|---|
| **Job Security Level** | **Frequency** | **Percentage (%)** | **Mean Risk Tolerance Score** |
| Very High (Completely Secure) | 52 | 12.6 | 32.4 |
| High (Mostly Secure) | 128 | 31.1 | 28.6 |
| Moderate (Somewhat Secure) | 156 | 37.9 | 24.2 |
| Low (Insecure) | 56 | 13.6 | 19.8 |
| Very Low (Highly Insecure) | 20 | 4.9 | 16.5 |

## Financial Decision-Making Styles

Table 7 reveals that analytical/research-based decision-making was most prevalent (45.1%), followed by dependent/advisor-driven (27.2%) and intuitive styles (23.8%). Importantly, analytical investors achieved the highest mean portfolio returns (14.2%), while spontaneous/impulsive investors underperformed (8.4%). This performance differential underscores the value of structured financial education and evidence-based investment processes.

| TABLE 7<br>FINANCIAL DECISION-MAKING STYLES OF PORTFOLIO INVESTORS (N = 412) | | | |
|---|---|---|---|
| **Decision-Making Style** | **Frequency** | **Percentage (%)** | **Mean Portfolio Return (%)** |
| Analytical / Research-Based | 186 | 45.1 | 14.2 |
| Intuitive / Gut-Feeling | 98 | 23.8 | 11.8 |
| Dependent / Advisor-Driven | 112 | 27.2 | 12.6 |
| Spontaneous / Impulsive | 42 | 10.2 | 8.4 |
| Avoidant / Delayed | 24 | 5.8 | 6.2 |



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## Correlation Analysis

Table 8 presents the Pearson correlation matrix. Financial risk tolerance exhibited strong positive correlations with financial literacy (r = 0.62), time horizon (r = 0.58), income (r = 0.56), and job security (r = 0.51). A significant negative correlation with behavioral biases (r = –0.38) confirms that cognitive distortions constrain risk-taking capacity. Age displayed a negative correlation with risk tolerance (r = –0.34), consistent with life-cycle predictions.

**TABLE 8**
**PEARSON CORRELATION MATRIX OF KEY VARIABLES (N = 412)**

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1. FRT | 1 | | | | | | |
| 2. FL | 0.62*** | 1 | | | | | |
| 3. TH | 0.58*** | 0.47*** | 1 | | | | |
| 4. Income | 0.56*** | 0.41*** | 0.38*** | 1 | | | |
| 5. JS | 0.51*** | 0.36*** | 0.33*** | 0.44*** | 1 | | |
| 6. BB | –0.38*** | –0.42*** | –0.29*** | –0.21** | –0.25*** | 1 | |
| 7. Age | –0.34*** | –0.18** | –0.31*** | 0.22** | 0.15* | 0.09 | 1 |

## Multiple Regression Analysis

Table 9 reports the multiple regression results predicting financial risk tolerance. The model achieved strong explanatory power ($R^2 = 0.682$, Adjusted $R^2 = 0.674$, $F = 84.26$, $p < .001$). Financial literacy emerged as the strongest predictor ($\beta = 0.35$, $p < .001$), followed by time horizon ($\beta = 0.31$, $p < .001$), job security ($\beta = 0.26$, $p < .001$), and income ($\beta = 0.28$, $p < .001$). Behavioral biases exerted a significant negative effect ($\beta = –0.19$, $p < .001$). All Variance Inflation Factor (VIF) values were below 2.0, indicating absence of multicollinearity.

**TABLE 9**
**MULTIPLE REGRESSION ANALYSIS: PREDICTORS OF FINANCIAL RISK TOLERANCE (N = 412)**

| Variable | B (Unstd.) | SE | β (Std.) | t-value | p-value | VIF |
|---|---|---|---|---|---|---|
| (Constant) | 8.42 | 1.86 | — | 4.53 | < .001 | — |
| Investment Goals (IG) | 0.28 | 0.08 | 0.18 | 3.42 | 0.001 | 1.68 |
| Time Horizon (TH) | 0.46 | 0.09 | 0.31 | 5.18 | < .001 | 1.82 |
| Perceived Job Security (JS) | 0.38 | 0.07 | 0.26 | 5.29 | < .001 | 1.54 |
| Financial Decision-Making (DM) | 0.32 | 0.08 | 0.22 | 4.12 | < .001 | 1.76 |
| Behavioral Biases (BB) | -0.24 | 0.06 | -0.19 | -3.89 | < .001 | 1.92 |
| Financial Literacy (FL) | 0.52 | 0.09 | 0.35 | 5.82 | < .001 | 1.88 |
| Age | -0.18 | 0.05 | -0.16 | -3.24 | 0.001 | 1.42 |
| Annual Income | 0.34 | 0.07 | 0.28 | 4.78 | < .001 | 1.64 |
| Investment Experience | 0.22 | 0.06 | 0.20 | 3.68 | < .001 | 1.58 |
| Gender (Male=1) | 0.42 | 0.11 | 0.15 | 3.85 | < .001 | 1.36 |

*Model Fit: $R^2 = 0.682$, Adjusted $R^2 = 0.674$, $F = 84.26$ ($p < .001$), Durbin–Watson = 1.92*

These findings align with (Verma et al., 2025), who demonstrated that financial literacy recontextualizes risk as manageable rather than threatening, thereby enhancing calculated risk-taking. The negative beta for behavioral biases supports (Gupta , 2025) and the (IIMB



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Management Review, 2024), confirming that loss aversion and herding systematically suppress risk tolerance even among educated investors.

## MANOVA Results

Table 10 presents the MANOVA results examining demographic effects on the combined dependent variables (risk tolerance, investment goals, time horizon, job security, and decision-making quality). Gender (Wilks' $\lambda = 0.912$, $F = 4.82$, $p < .001$, partial $\eta^2 = 0.057$), age group (Wilks' $\lambda = 0.784$, $F = 3.56$, $p < .001$), and income group (Wilks' $\lambda = 0.802$, $F = 3.42$, $p < .001$) all demonstrated significant multivariate effects. Education and occupation also achieved significance, while interaction effects (Gender × Age, Gender × Income) were non-significant.

**TABLE 10**
**MULTIVARIATE ANALYSIS OF VARIANCE (MANOVA): DEMOGRAPHIC EFFECTS ON RISK DIMENSIONS (N = 412)**

| Effect | Wilks' λ | F-value | df1 | df2 | p-value | Partial η² | Observed Power |
|---|---|---|---|---|---|---|---|
| Intercept | — | — | — | — | — | — | — |
| Gender | 0.912 | 4.82 | 5 | 398 | < .001 | 0.057 | 0.982 |
| Age Group | 0.784 | 3.56 | 15 | 1194 | < .001 | 0.042 | 0.998 |
| Education Level | 0.856 | 2.98 | 15 | 1194 | 0.001 | 0.036 | 0.994 |
| Income Group | 0.802 | 3.42 | 15 | 1194 | < .001 | 0.041 | 0.997 |
| Occupation | 0.834 | 2.76 | 15 | 1194 | 0.001 | 0.033 | 0.978 |
| Investment Experience | 0.876 | 2.34 | 15 | 1194 | 0.002 | 0.028 | 0.956 |
| Gender × Age | 0.942 | 1.86 | 5 | 398 | 0.098 | 0.023 | 0.524 |
| Gender × Income | 0.928 | 2.12 | 5 | 398 | 0.068 | 0.026 | 0.612 |
| Error | — | — | — | — | — | — | — |

## DEA Efficiency Analysis

Table 11 applies Data Envelopment Analysis to evaluate the efficiency of investor categories. High financial literacy investors achieved the highest efficiency scores (CRS = 0.95, VRS = 0.97), indicating optimal conversion of risk inputs into portfolio returns. Conversely, low financial literacy investors exhibited substantial inefficiency (CRS = 0.72, VRS = 0.78). Young tech professionals and self-employed entrepreneurs demonstrated increasing returns to scale, suggesting that expanded investment activity would yield disproportionate efficiency gains. Retired investors displayed decreasing returns to scale, consistent with conservative, capital-preservation mandates.

**TABLE 11**
**DATA ENVELOPMENT ANALYSIS (DEA): EFFICIENCY OF INVESTOR CATEGORIES (N = 412)**

| Investor Category (DMU) | Inputs | Outputs | CRS Eff. | VRS Eff. | Scale Eff. | Returns to Scale |
|---|---|---|---|---|---|---|
| Young Tech Professionals (18–30) | Risk Aversion, Time Constraint | Portfolio Returns, Diversification | 0.82 | 0.88 | 0.93 | IRS |
| Mid-Career Salaried (31–45) | Moderate Risk, Balanced Time | Steady Returns, Asset Growth | 0.91 | 0.94 | 0.97 | CRS |



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| | | | | | | |
|---|---|---|---|---|---|---|
| Senior Executives (46–60) | Low Risk Aversion, High Experience | Wealth Preservation, Income | 0.78 | 0.84 | 0.93 | DRS |
| Retired Investors (> 60) | High Risk Aversion, Limited Time | Capital Safety, Liquidity | 0.65 | 0.72 | 0.90 | DRS |
| Self-employed Entrepreneurs | High Risk Tolerance, Variable Income | High Returns, Growth | 0.88 | 0.92 | 0.96 | IRS |
| Female Investors | Moderate Risk, Long-term Focus | Stable Returns, Security | 0.84 | 0.89 | 0.94 | IRS |
| Male Investors | Higher Risk, Diverse Portfolio | Aggressive Returns, Diversification | 0.89 | 0.93 | 0.96 | CRS |
| High Financial Literacy | Low Bias, High Knowledge | Optimal Returns, Efficiency | 0.95 | 0.97 | 0.98 | CRS |
| Low Financial Literacy | High Bias, Low Knowledge | Suboptimal Returns | 0.72 | 0.78 | 0.92 | IRS |

## Gender Differences

Table 12 confirms significant gender differences across all major variables. Male investors reported higher risk tolerance (M = 28.42, SD = 6.18) than female investors (M = 24.18, SD = 5.94), with a large effect size (Cohen's d = 0.70). Males also exhibited superior financial literacy scores, greater portfolio diversification, and higher annual returns. These findings resonate with (Sengupta &Mitra,2025) and (Bhattacharyya, 2024), while also suggesting that Bengaluru's technology sector—despite its progressive employment culture—has not fully eliminated gender-based financial behavior disparities.

**TABLE 12**
**GENDER DIFFERENCES IN FINANCIAL RISK TOLERANCE AND RELATED VARIABLES (N = 412)**

| Variable | Male (n=268) | Female (n=144) | t-value | df | p-value | Cohen's d |
|---|---|---|---|---|---|---|
| Financial Risk Tolerance | 28.42 (6.18) | 24.18 (5.94) | 6.82 | 410 | < .001 | 0.70 |
| Investment Goal Aggressiveness | 3.82 (0.74) | 3.24 (0.82) | 7.24 | 410 | < .001 | 0.74 |
| Time Horizon (Years) | 6.84 (3.12) | 5.42 (2.88) | 4.56 | 410 | < .001 | 0.48 |
| Perceived Job Security | 3.68 (0.92) | 3.42 (0.88) | 2.88 | 410 | 0.004 | 0.29 |
| Financial Literacy Score | 72.4 (14.2) | 66.8 (15.6) | 3.68 | 410 | < .001 | 0.38 |
| Portfolio Diversification Index | 0.68 (0.18) | 0.58 (0.20) | 5.12 | 410 | < .001 | 0.52 |
| Behavioral Bias Score | 32.4 (8.6) | 28.6 (7.8) | 4.68 | 410 | < .001 | 0.47 |
| Annual Portfolio Return (%) | 14.8 (5.2) | 12.4 (4.6) | 4.92 | 410 | < .001 | 0.49 |

## Age Group Differences

Table 13 presents the One-Way ANOVA results. Significant age differences emerged for risk tolerance ($F = 13.22$, $p < .001$, partial $\eta^2 = 0.089$), investment goal aggressiveness ($F =$



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13.54, p < .001), and portfolio returns (F = 11.32, p < .001). Post-hoc comparisons (Tukey HSD) revealed that investors aged 18–30 exhibited significantly higher risk tolerance than all older groups, while those above 60 displayed the most conservative profiles.

**TABLE 13**
**ONE-WAY ANOVA: AGE GROUP DIFFERENCES IN KEY FINANCIAL VARIABLES (N = 412)**

| Variable | 8–30 (n=98) | 31–45 (n=186) | 46–60 (n=89) | >60 (n=39) | F | p | $h^2$ |
|---|---|---|---|---|---|---|---|
| Risk Tolerance | 29.86 (5.92) | 27.14 (6.08) | 24.68 (5.74) | 21.42 (5.36) | 13.22 | <.001 | 0.089 |
| Goal Aggressiveness | 3.94 (0.71) | 3.62 (0.78) | 3.28 (0.81) | 2.86 (0.76) | 13.54 | <.001 | 0.091 |
| Time Horizon (yrs) | 7.82 (2.94) | 6.48 (3.02) | 5.36 (2.76) | 4.12 (2.48) | 12.48 | <.001 | 0.084 |
| Portfolio Return (%) | 15.6 (5.1) | 14.2 (4.9) | 12.8 (4.6) | 10.4 (4.2) | 11.32 | <.001 | 0.077 |
| Financial Literacy | 74.8 (13.6) | 71.2 (14.4) | 68.4 (15.1) | 62.6 (16.2) | 7.86 | <.001 | 0.055 |
| Behavioral Bias | 34.2 (8.1) | 31.8 (8.4) | 29.6 (7.9) | 27.4 (7.2) | 6.94 | <.001 | 0.049 |

## Education and Income Effects

Table 14 demonstrates that risk tolerance increases monotonically with education level, from undergraduates (M = 21.4) to doctorate holders (M = 27.8). Table 15 reveals that equity allocation rises with income (from 12.4% in the < 5 lakhs group to 42.8% in the > 20 lakhs group), while fixed deposit preference declines correspondingly (from 38.2% to 12.6%). These patterns confirm that both human capital and financial resources are necessary conditions for translating risk willingness into risky asset ownership.

**TABLE 14**
**RISK TOLERANCE DISTRIBUTION BY EDUCATION LEVEL (N = 412)**

| Education Level | Very Low Risk | Low Risk | Moderate Risk | Above Average Risk | High Risk | Mean Score | Std. Dev. |
|---|---|---|---|---|---|---|---|
| Undergraduate (n=76) | 12 | 18 | 32 | 10 | 4 | 21.4 | 5.2 |
| Postgraduate (n=198) | 8 | 22 | 82 | 58 | 28 | 25.8 | 5.8 |
| Professional Degree (n=102) | 4 | 10 | 42 | 32 | 14 | 26.2 | 6.1 |
| Doctorate (n=36) | 2 | 4 | 14 | 10 | 6 | 27.8 | 6.4 |

**TABLE 15**
**ASSET ALLOCATION PREFERENCES BY ANNUAL INCOME GROUP (N = 412)**

| Annual Income (INR) | n | Equity (%) | Mutual Funds / SIPs (%) | Fixed Deposits (%) | Other / Debt (%) | Mean Risk Tolerance |
|---|---|---|---|---|---|---|
| < 5 Lakhs | 45 | 12.4 | 28.6 | 38.2 | 20.8 | 21.8 |
| 5–10 Lakhs | 112 | 22.6 | 34.8 | 28.4 | 14.2 | 24.6 |



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| | | | | | | |
|---|---|---|---|---|---|---|
| 10–20 Lakhs | 168 | 34.2 | 36.4 | 18.6 | 10.8 | 27.4 |
| > 20 Lakhs | 87 | 42.8 | 32.1 | 12.6 | 12.5 | 29.8 |
| **Overall** | **412** | **30.1** | **34.2** | **22.4** | **13.3** | **26.5** |

## DISCUSSION

The findings of this study contribute to behavioral finance theory in three significant ways. First, they establish that financial literacy functions as the primary catalyst for risk tolerance in emerging market contexts. Unlike studies in developed markets where risk tolerance is often treated as a stable personality trait, the Bengaluru data suggest that risk tolerance is highly malleable and responsive to educational interventions. This has direct policy implications: expanding structured financial literacy programs—particularly those addressing compound interest, inflation, and diversification—could materially enhance market participation and portfolio efficiency.

Second, the study documents the dual-edged nature of Bengaluru's digital investment revolution. While fintech platforms have democratized access, they have also amplified behavioral biases among younger, less experienced investors. The strong correlation between herding behavior and investment decisions ($r = 0.47$) aligns with (Gupta, 2025) and suggests that social media-driven "finfluencer" culture may be inducing suboptimal portfolio allocations. Regulatory frameworks should consider behavioral risk disclosures and cooling-off periods for high-risk digital asset categories.

Third, the DEA analysis introduces a novel efficiency lens to risk tolerance research. By demonstrating that high-literacy investors achieve near-optimal efficiency (CRS = 0.95) while low-literacy investors lag significantly (CRS = 0.72), the study bridges the gap between psychological profiling and performance outcomes. This efficiency framework can guide robo-advisory algorithms in tailoring not just risk-appropriate portfolios, but efficiency-maximizing investment pathways.

The persistent gender gap in risk tolerance, despite Bengaluru's progressive technology sector, warrants targeted intervention. Women investors' preference for fixed deposits and insurance products—while prudent—may result in long-term wealth erosion due to inflation. Gender-sensitive financial advisory, female-focused investment communities, and workplace financial wellness programs could help narrow this gap.

## CONCLUSION

This study provides a comprehensive empirical assessment of financial risk tolerance among 412 portfolio investors in Bengaluru, integrating demographic profiling, psychometric measurement, and efficiency analysis. The key conclusions are:

- Financial literacy is the strongest predictor of risk tolerance, suggesting that education-based interventions can materially alter investor behavior.
- Behavioral biases significantly suppress risk tolerance, with loss aversion and herding representing the most detrimental distortions.
- Gender and age differences remain pronounced, requiring segmented advisory approaches.
- Perceived job security and time horizon are critical situational determinants that financial planners must assess systematically.
- DEA efficiency analysis reveals substantial performance heterogeneity across investor categories, with literacy-driven investors achieving optimal risk-adjusted returns.



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For practitioners, the findings underscore the need for hybrid advisory models that combine algorithmic portfolio construction with behavioral coaching. For policymakers, the results support mandates for behavioral risk disclosures in digital investment platforms and expanded financial literacy curricula. For researchers, the integrated methodology offers a replicable framework for examining risk tolerance in other emerging market contexts.

## LIMITATIONS AND FUTURE RESEARCH

The study is cross-sectional, limiting causal inference. Future research should employ longitudinal designs to track how risk tolerance evolves across market cycles. The purposive sampling technique, while appropriate for Bengaluru's investor population, may limit generalizability to tier-2 and tier-3 Indian cities. Additionally, the reliance on self-reported risk tolerance may introduce social desirability bias; future studies should incorporate incentivized behavioral measures or portfolio-level objective data.

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